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Automatic Speech Recognition for Low-Resource and Morphologically Complex Languages

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Automatic Speech Recognition for Low-Resource and Morphologically Complex Languages

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Abstract

The application of deep neural networks to the task of acoustic modeling for automatic speech recognition (ASR) has resulted in dramatic decreases of word error rates, allowing for the use of this technology in smart phones and personal home assistants in high-resource languages. Developing ASR models of this caliber, however, requires hundreds or thousands of hours of transcribed speech recordings, which presents challenges for most of the world's languages. In this work, we investigate the applicability of three distinct architectures that have previously been used for ASR in languages with limited training resources. We tested these architectures using publicly available ASR datasets for several typologically and orthographically diverse languages, whose data was produced under a variety of conditions using different speech collection strategies, practices, and equipment. Additionally, we performed data augmentation on this audio, such that the amount of data could increase nearly tenfold, synthetically creating higher resource training. The architectures and their individual components were modified, and parameters explored such that we might find a best-fit combination of features and modeling schemas to fit a specific language morphology. Our results point to the importance of considering language-specific and corpus-specific factors and experimenting with multiple approaches when developing ASR systems for resource-constrained languages.

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Chapter 1

Introduction and Motivation

1.1 Introduction and Motivation

Automatic speech recognition (ASR) is the process by which audio input is taken and transcribed to text, for use in many modern technologies such as Amazon's Alexa, Google Assistant, or Apple's Siri. The ability to accurately detect and convert these spoken words into linguistic data is quite lucrative and sought after by large corporations for use in product development, as the spoken word is roughly 3 times faster than keyboard input [5]. The realm of speech recognition and transcription has been explored for over 60 years and is just recently being converted to the deep learning realm from the traditional statistical based models. This switch allows for the traditional deep learning architectures and design processes to take place, with revolutions occurring every few years as companies develop new, application specific models. However, these ASR pipelines require hundreds, if not thousands, of hours of data [2, 6]; a corpus of this size does not exist for a large majority of the 7,117 languages, especially as over 40% are endangered, with less than 1,000 speakers [7]. In addition to the shear amount of raw audio data necessary for prediction, a large collection of written text must be available for appropriate constraint and correction of this output - another limiting factor.

These existing architectures can be adapted to a low-resource setting using tech-

niques such as transfer learning and data augmentation, but challenges remain. Not every implementation, pipeline, or weighted staging will fit the characteristics of a target language. As such, the motivation of this thesis is to expand upon the current deep learning implementations of low-resource speech recognition [8, 9, 10] through a study against small and diverse ASR training corpora. The final result will be a pipeline capable of accepting an under-resourced language, determining the appropriate model parameters based on the based on the features of the language and the corpus, such as morphological complexity, orthographic system, speaker diversity, and recording quality, and producing character-based transcriptions from the input data. Specifically, the principal contributions of this thesis are outlined as follows:

- Examine the diverse field of current automatic speech recognition technologies and evaluate their effectiveness across several diverse languages.
- Input feature comparison for language size and morphologies.
- State of the art convolutional model architecture optimization.
- Purposeful dataset re-partitioning to remove the natural disjoint speaker implementations.

1.2 Document Structure

The remainder of this document is organized as follows:

- Chapter 2 reviews the background of ASR, including feature extraction, model types, and related works.
- Chapter 3 breaks down the language corpora used in this thesis.
- Chapter 4 describes the methodology and approach towards developing a novel low resource language transcriber.

- Chapter 5 outlines the experimental results and performance across languages.
- Chapter 6 summarizes the key concepts and diagrams potential future work.

Chapter 2

Background

2.1 Introduction

This chapter describes the basics of ASR, deep learning construction, and prior work.

2.2 Automatic Speech Recognition

Automatic speech recognition is the process of transcribing speech into characters via a computer program, and generally follows the following three-pronged course of action: feature extraction, acoustic modelling, and then language modelling, depicted visually in Figure 2.1. The low-resource scenario is broadly defined as any language corpora where the amount of acoustic data roughly totals to less than 20 hours, and is not constrained by the amount of global speakers.

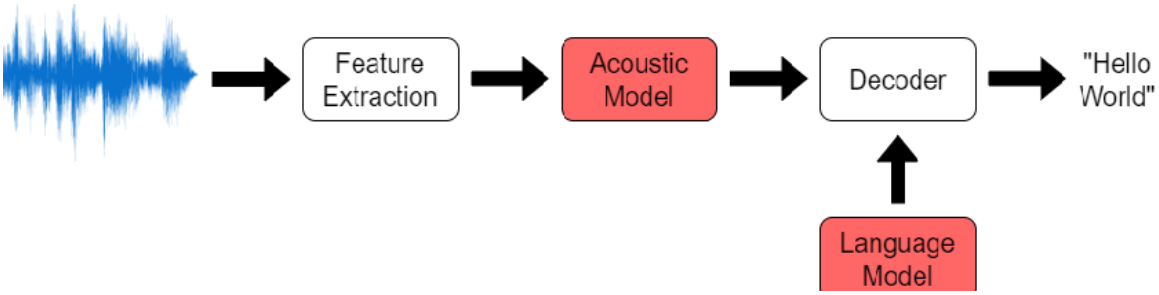

Figure 2.1: Generic pipeline of an ASR system.

A speech signal is transformed through some measure, whether it be statistical or

deep learning, into a small window of time meant to capture into a small window of time with stable acoustic properties that more easily be associated with an individual speech sound, or phoneme. This is then passed into an acoustic model, Gaussian Mixture Model (GMM), Deep Neural Network (DNN), etc., which generally uses some sort of mechanism to capture temporal data, before predicting a character/sequence of characters. A decoder, in most cases relying on a language model that models likely words and word sequences, is then applied to make sure that this prediction is a valid combination of characters for the language and is likely to occur; this final result is then output to the user.

2.3 Feature Extraction

In deep learning, this raw wave form may be passed directly into the deep learning model [11, 12, 13, 14], however these systems produce marginally worse (1-2%) results as opposed to using hand-crafted features. These hand-crafted features aim to emulate the brain's auditory response to sound, and although there are concerns they may hinder speaker characteristic extraction [12], traditional state-of-the-art methods [15, 16] seem unhindered. Additionally, research is being conducted into making these hand-crafted features [17], more capable of aptly capturing speaker embeddings. An overview of the most basic pre-processing techniques is shown in Figure 2.2.

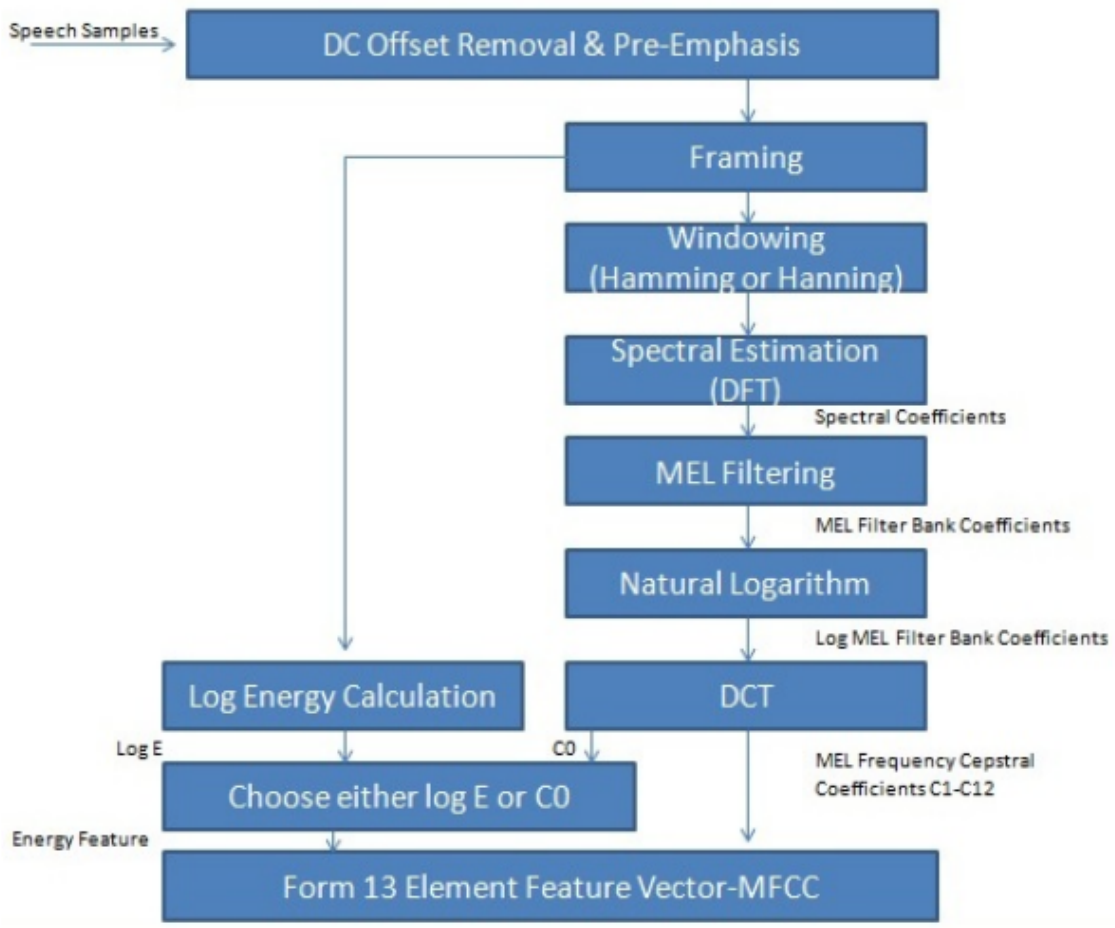

Figure 2.2: An overview of the most basic feature extraction process, including the different stopping points for various features [1].

2.3.1 Spectral Features

The most basic features are meant to visualize the short time power spectrum, which contains data about the vocal tract and are meant to depict human speech perception. First, DC offset removal and pre-emphasis is applied due to the rapid decay of an audio signal. This boosts the energy of the signal, emphasizing the higher frequency components which are more likely to contain speech. Next, these features are divided into small time-scale data, to attempt to capture a morpheme; typically, a value of 20-40 ms is used. A window function, generally Hamming, is applied to taper the frames as opposed to harsh segmentation, allowing for the potential capture across

multiple frames. This data is converted into several discrete frequencies via a Fourier transform, to determine the spectral density of the audio. Often such information is too finely calculated when compared to the data interpreted by the human ear; therefore, data is grouped at certain frequencies, calculated via the sampling rate, to emphasize the frequencies not at the extrema.

Before additional filtering is applied, the features can be extracted at this stage: the spectral coefficients. These are not often used, as the filtering stages remove frequencies unperceived by humans, but in systems where less modified data is desired [18] they can produce quality results.

2.3.2 Mel Filterbanks

Mel filtering occurs via the following Equation 2.1 and was introduced by Stevens and Volkmann [19] as a way to mimic the way human speech perception attends to specific frequency bands.

$$mel(f) = 1127 * ln(1 + \frac{f}{700}) \tag{2.1}$$

Additionally, the natural logarithm can be applied again, further normalizing the filterbanks left in a highly correlated fashion; referred to as logmel filterbanks. This data can be used as an input to the system in the hopes of maintaining the highly correlated temporal information in the deep learning model.

2.3.3 Mel-frequency Cepstral Coefficients (MFCCs)

The final calculation is to take the discrete cosine of these log energies to decorrelate these overlapping values [20, 21].

These features themselves carry no time-based information and in the speech realm, adding the delta coefficients, allow the system to model some temporal information in a time independent situation. The order of the MFCCs is determined to

be 12 with 1 measure of overall energy, as additional orders determined not helpful in ASR applications [20].

2.3.4 Feature Space Maximum Likelihood Linear Regression (fMLLR)

One important notion to consider when building deep learning systems is overfitting to the training data. In images this can occur with respect to the background, and in audio with respect to the speaker themself. Thus, speaker normalization is considered to minimize the potential of overfitting to a speaker's audio characteristics. This is accomplished through Maximum Likelihood Linear Regression (MLLR), where the means of the Gaussian are transformed via the average of the feature, where the estimators are produced based on this likelihood [22].

FMLLR is a constrained MLLR, meaning it is calculated in a similar manner, except including an extended transformation matrix and observation vector, and applying the transformation on the variance as opposed to the mean [23].

2.3.5 I/X Vector

I-Vectors are information taken from a Gaussian Mixture Model (GMM) system which has been trained on the full corpus. In the GMM space, no distinctions are made between speaker and channel effects, thus assuming that every utterance has been produced by a new speaker [24]. Then, with Principal Component Analysis (PCA) and normalization, i-vectors are extracted per speaker. These i-vectors are extracted, and their dimension reduced via Linear Discriminant Analysis (LDA), before able to be used as inputs [25] to the deep learning model.

X-Vectors are similar in nature to i-vectors, except taken from a deep neural network (DNN) that is trained to discriminate between speakers. This DNN takes in filterbanks and classifies speakers based on this data; x-vectors are extracted from a convolutional layer before dimensional reduction occurs within the neural network

layers [26, 17]. In a Cantonese ASR system, these x-vectors were able to produce 2-3% equal error-rate (EER) reductions as opposed to i-vector based systems but require an additional training step to produce the input data.

2.4 Acoustic Models

Over time, two main categories of models have risen to prominence, statistical and deep learning, with their derivatives producing nearly every state-of-the-art result.

2.4.1 Hidden Markov Model

A Markov model is a finite-state system where the behavior depends on the current state as a method of predicting the next state. Whenever the state transition information is not directly evident or the states are not observable, this is referred to as a Hidden Markov Model (HMM). Speech is temporally dependent, which HMMs are able to model through self-loops, and predict the speech, typically via the Viterbi or some dynamic programming algorithm, to find the most likely next character or phone. The forward and backward algorithms are used to update the internal probabilities of each state transition, allowing for the HMM to update the internal weights, similar to propagation in a DNN. Referred to as the EM step, the parameters can be easily iterated and increase the internal state of the HMM's convergence rate [27]. Models for sentences can be formed through the concatenation of the phone HMMs, allowing the prediction of a string of phones [28].

2.4.2 Gaussian Mixture Model

Gaussian mixture models (GMM) systems are combined alongside the HMM to estimate the density and maximum the likelihood of the data's distribution. If the weights are allowed to vary slightly in the subspace, but share a global mapping, this is referred to as a Subspace Gaussian Mixture Model (SGMM) [29]. Subspaces

are introduced as opposed towards using larger models as a means of reducing the number of parameter estimation issues by reducing the dimensionality of the system [30].

Although capable of producing high quality results, the noted issue with GMMs is that they are inefficient at modeling non-linear data [31]. Thus, speech, with its inflection, tone, and other properties are not the ideal application.

2.4.3 Deep Neural Network

Deep neural networks are incredibly prevalent in industry applications as a method of classification and recognition. Through the stacking of hidden layers on large amounts of data, better predictions can be made on the non-linear data as there is no concept of spatial representation. Each hidden layer uses an activation function, often a Rectified Linear Unit (ReLU), to map the weights to a standardized state. For multiclass classification, such as predicting characters in an ASR system, a softmax nonlinearity, Equation 2.2, is applied to normalize the output to a probability distribution across the classes.

$$\sigma(x)_i = \frac{exp(x_i)}{\sum_j exp(x_j))} \tag{2.2}$$

DNNs are trained via forward and backward propagations of the derivatives of the difference between the training and expected data, where the difference is calculated via cross entropy loss, Equation 2.3, where p is the target probability of each character.

$$C = -\sum_j d_j \log p_j \tag{2.3}$$

As there is often a lot of data in a training set, it is generally more efficient to operate on a batch scale, updating the weights in smaller quantities as opposed to after processing the entire set. There are several optimizers available, e.g., Adam,

Stochastic Gradient Descent (SGD), etc., which smooth the gradient per batch such that large jumps do not occur too quickly, proportionally introducing these updated weights.

DNNs with many hidden layers can take thousands of iterations to optimize successfully [32]; therefore, often weight initialization is applied through methods like unsupervised pre-training [33] or transfer learning [34], such that the backward propagation magnitudes are not incredibly large.

As speech is incredibly time dependent, something with which traditional convolutional neural networks do not bother, architectures have been proposed that modify these convolutional constructions to include a concept called Attention [35] by relating the positions of a sequence to compute its entire representation. Through this concept, offshoots of the traditional DNN can be created, notably the Transformer model.

2.4.4 Recurrent Neural Networks

The drawback of DNNs is that they require a fixed dimensionality vector and for sequential data, a conglomerate mapping of these sequences is not entirely feasible in a generic sense. As such, architectures have arisen, called Long-Short Term Memory (LSTM) and Recurrent Neural Networks (RNNs) [36, 37] which specialize in modeling the data per timestep. These can be incredibly effective at predicting speech when there is lots of input data available [38] but are notoriously difficult to train [39] due to the long-range dependencies and vanishing and exploding gradient problems during propagation. Modern RNN and LSTM networks are capable of producing quality results [40], but still require thousands of hours of data and are not capable of beating DNNs in the low-resource environment [41].

2.5 Language Models

Whatever model implemented, whether it be statistical or deep learning based, it will output a string of characters or words that it feels best fits the audio signal. This information, by itself, is often inaccurate due to the similarity between phone pronunciation, especially given the speaker variability. A language model is used to convert this data into a more realistic sequences via rescoring the prediction based on a corpus of text from the language of choice. Language models analyze the textual data and estimate the probability of a word sequence occurring; thus, can replace predictive words with what the language model has seen more commonly in the data.

2.5.1 N-Gram

The typical language model used is an n-gram type, where n is between 1 and 5. In this case n refers to the depth of the probability search, looking n - 1 words back. The probability is calculated via the chain rule and maximum likelihood estimate for every word in the corpus, thus predicting the next most common word following a specific word or sequence of words [42].

2.5.2 Neural

The n-gram model is successful but falls victim to the curse of dimensionality past n=5 as the number of words it must keep track of grows significantly, with little reduction in the predictive ability. Long short-term memory (LSTM) language models are able to capture the long-term information more efficiently than n-gram models, and although the calculation of the probability takes longer, the predictive ability is better because of the infinite history states [43]. Recurrent neural networks (RNN) can also be used for this task, but the context range is more limited due to the vanishing gradient problem.

2.5.3 Trans-dimensional Random Field (TRF)

There is a third explored language model, the trans-dimensional random field model. By mixing a collection of random fields in different dimensions, allowing for larger width and depth of the data connectivity [11]. These models learn through stochastic approximation and perform a similar Markov updating sequence as in the HMM systems. These are an interesting application of non-deep learning language modeling, but do not produce equivalent rates to the LSTM LM.

2.6 Data Augmentation

2.6.1 Pitch/Speed/Noise

Most of the ASR architecture work proceeds with hundreds or thousands of hours of audio data but collecting speech corpora of this size is time-consuming and expensive. As a result, available speech corpora for many languages have fewer than 20 hours of transcribed audio suitable for acoustic model training. In these cases, we can modify the data using traditional acoustic methods, such as the Pitch-Synchronous Overlap-Add (PSOLA) [44, 45] approach for pitch shifting directly in the time domain, which keeps the original audio's tempo, adjusting the timbre.

Additionally, time-stretching [46] can be applied to make the original audio sound as if it were spoken at a different tempo, maintaining the original timbre. Traditional methods include Waveform Similarity Overlapp-Add (WSOLA) and phase vocoder, with the note of caution that a reduction of artifacts can be introduced when modifying the original audio.

Lastly, noise additions, e.g., fan, barking, etc. can be incorporated into the audio data [47] as a method of artificially generating new training data. However, research into noise robust systems have concluded that some methods such as Wiener filtering and spectral subtraction are satisfactory at compensating the features for this noise

and deep, wide hidden layers of a DNN naturally normalize heterogenous data [48]. Therefore, it may be substantially less beneficial to introduce these elements of noise as opposed to traditional music based alterations in the training set, because of the duplication of audio. It still may be favorable for the overall system if noise were introduced into the test set to reduce overfitting.

2.6.2 SpecAugment

In addition to the time-domain based mutations, frequency-domain based masks can be applied to the audio signal to introduce regularization and helps the network emphasize robustness. These methods are referred to as time and frequency masking [2], where consecutive time steps or frequency bands are nulled out, depicted in Figure 2.3, to add this element of regularization.

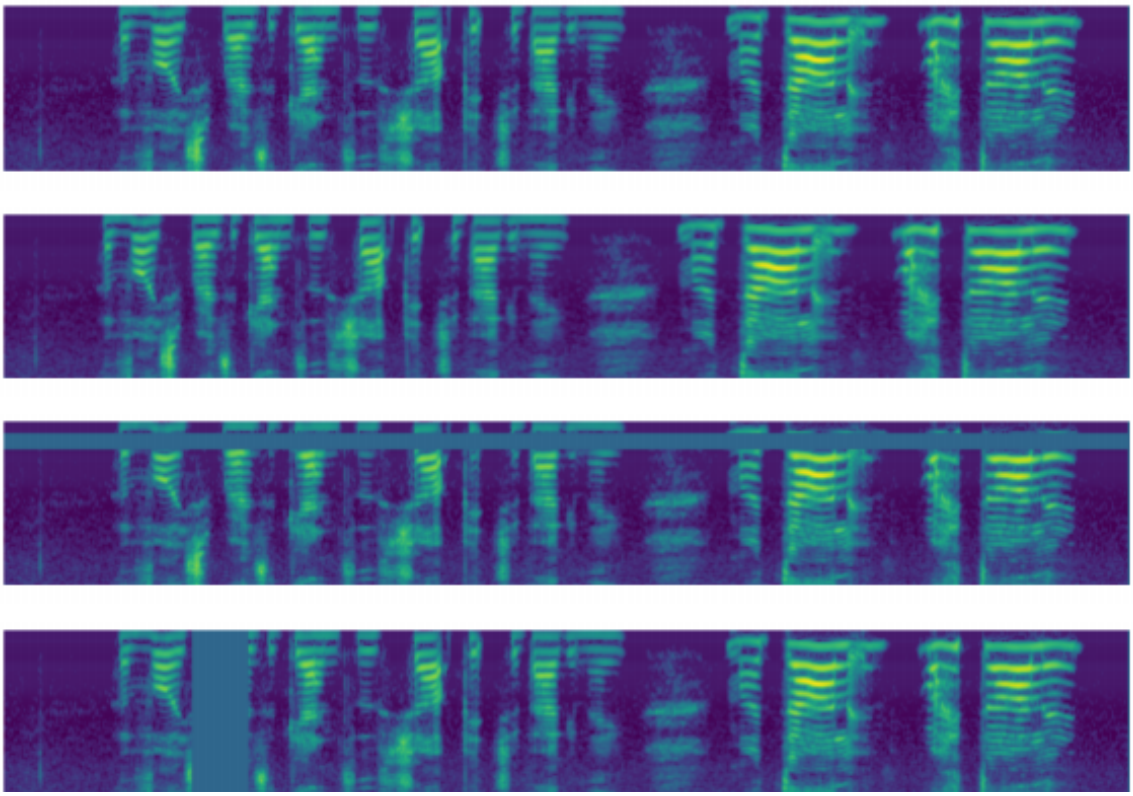

Figure 2.3: Augmentations applied to the base input, given at the top. From top to bottom, the figures depict the log mel spectrogram of the base input with no augmentation, time warp, frequency masking and time masking applied [2]

.

2.6.3 Speech Synthesis

In a low-resource setting, the ability to generate data that may be for the training process is invaluable. Providing the model with additional data in a data-dependent environment allows for a better opportunity at a higher classification rate.

2.6.3.1 Tacotron

Tacotron 2 is a neural network architecture that allows for the speech synthesis of textual data. Using mel spectrograms and an encoder/decoder network, the weights are learned before using a WaveNet Vocoder to produce the waveforms [49]. This is an incredibly deep network and the number of iterations required for successful

synthesis on a large dataset is quite high; although, studies have reproduced quality synthetic data with a small training set of 1 hour and fewer [50], the training time and resources required is still large.

2.6.3.2 Festival

Festival [51] and its subsidiaries is the most popular non-neural speech synthesis, using statistical parametric speech synthesis and back ended by HMMs. Similar to language models, the non-neural performance is not as effective at producing indistinguishable synthesized speech; however, the speed and efficiency of this implementation implies a suitable alternative.

2.7 Evaluation Metrics

2.7.1 Character/Word Error Rate

ASR is typically evaluated according to the character and word error rates (CER, WER, respectively). When given a predicted and the expected sentence, the Levenshtein distance is calculated - the minimum number of transforms necessary to convert the predicted sentence into the reference. These transforms are either insertions (i), substitutions (s), or deletions (d), with a fourth option, contiguous character swaps, considered but held out of standardized calculations. The equation is identical for both character and word error rates, shown in Equation 2.4, where n is the total number of characters or words.

$$WER = \frac{i + s + d}{n} \tag{2.4}$$

2.7.2 Perplexity

When evaluating a language model, perplexity is used to provide a value on how well the model predicts the unseen sample. Perplexity is seen as the inverse of the probability predicted for this test sample, Equation 2.5.

$$P(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}} \tag{2.5}$$

2.8 Frameworks

2.8.1 Kaldi

Kaldi [52] is the most popular, open-source toolkit for creating speech recognition systems. The toolkit provides the ability for state-of-the-art feature extraction, acoustic modeling, language modeling, and decoding with continued work being conducted to improve the software. Kaldi feature extraction allows for the standard MFCC or perceptual linear prediction (PLP) features, but also work towards incorporating feature normalization to reduce the potential bias in the dataset through vocal tract length normalization (VTLN), cepstral mean and variance normalization, linear discriminant analysis (LDA), and more. The acoustic modeling allows for the easy creation of HMM, GMM, subspace GMM (SGMM), as well as neural models such as DNNs; often these are the state-of-the-art models used for comparison in low-resource settings. Built into the evaluation is a language modeling tool, using finite state transducers for any n-gram based LM. During the decoding process, lattice rescoring and other techniques can be applied to allow the use of neural language models as a second pass [53, 54].

2.8.2 DeepSpeech

DeepSpeech [15, 55] is an RNN based decoder system which produced state-of-the-art results that have now been superseded. The techniques used still provide valuable insight into methodology that can be beneficial in a low-resource environment. Their use of data augmentation, inducing noise and inflecting the pitch, is pivotal in the low resource environment. Additionally, their use of a bidirectional RNN, paired with Connectionist Temporal Classification (CTC) aligns the transcription with the audio [15], reducing potential silence and shortening the waveform. The DeepSpeech experiments required 11,940 hours of English data or 9,400 hours of Mandarin and required weeks of training time; this highlights the inability to apply RNNs to a low-resource scenario.

2.8.3 Wav2Letter/Wav2Vec

Wav2Letter [9, 56] provides a one-pass beam-search decoder with thresholding, pruning, and smearing capabilities for maximizing n-gram probabilities. The model architecture itself is a 12-layer convolutional neural network with incredibly large, fixed widths associated per layer, introducing training overhead. Such a model was capable of competitive results against standard corpora, but does not produce state-of-the-art.

Wav2Vec [57, 14] introduces feature encoder and transformer models to take in the raw audio input, learn the appropriate features, contextualize the data, before outputting the results. Unsupervised learning is first applied to the language, where discrete speech units [58] are first learned via a gumbel-softmax, before being passed into a multi-layer convolutional neural network as a means of audio encoding. These representations are passed into a Transformer network, quantized, and transformed into the final result via contrastive predictive coding [59]. Facebook does indicate state-of-the-art results on low-resource test sets of 10 minutes, 1 hour, and 10 hours; the key being unsupervised learning on a large dataset (960 hours) of the same lan-

guage, before finetuning on the small, labeled dataset, as well as using a transformer-based language model for decoding. These results likely will not generalize to the low-resource scenario where such an unsupervised learning schema can occur.

2.8.4 WireNet

WireNet [60] is a novel fully convolutional ASR architecture distinct from the other toolkits described prior and was developed specifically for the under-resourced language of Seneca, Figure 2.4. The architecture and associated training pipeline produced substantially lower word error rates for a 10-hour Seneca corpus than both DeepSpeech, trained using a transfer learning and data augmentation pipeline, and the most widely used architectures available in Kaldi. The main architectural feature is a stack of Inception [61] and ResNet [62] styled bottleneck blocks, with wide filter widths that emulate the temporal nature of audio. A multi-staged pipeline was employed with transfer learning from a high-resource language, transitioning into heavily augmented training data, before fine-tuning on the original, unaugmented data. This learning strategy allows for the neural network's weights to be better initialized as the network can use the larger datasets to converge more quickly, before being refined on the original, smaller dataset.

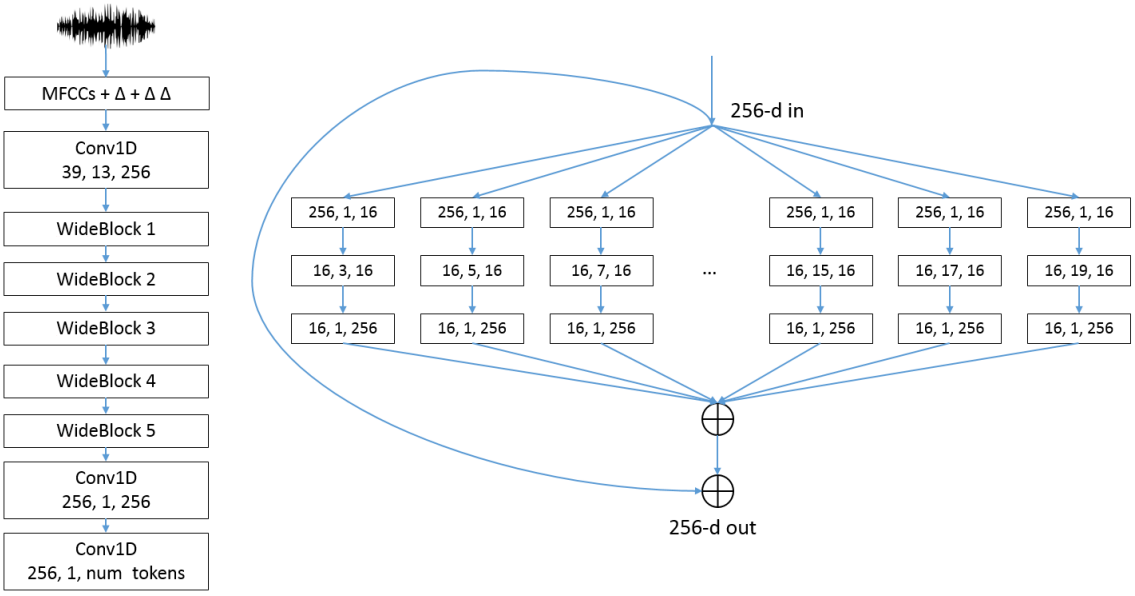

Figure 2.4: Left: The overall WireNet architecture. **Right:** A bottleneck block consisting of 9 paths, each with bottleneck filters centered by filters of different width to capture different temporal dependencies. Each layer shows (# input channels, filter width, # output channels).

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Chapter 3

Datasets

3.1 Amharic

3.1.1 Language Description

The Amharic (ISO 693-3 amh) language is a member of the Semitic branch of the Afro-Asiatic language family spoken by approximately 25 million people, primarily in Ethiopia. The Amharic writing system is based on the Ge'ez script, referred to as fidäl, and each symbol represents the combination of a character and a vowel, known as a CV syllable. Thus, the script consists of 231 distinct CV syllables, where words are formed via a root-pattern morphology, where affixes influence word construction. There are 38 phonemes, 31 consonants and 7 vowels, and are classified into the groups: stops, fricatives, nasals, liquids, and semivowels. The corpus [16] was collected in a closed environment via read speech from 124 native speakers, 70 male and 54 female, for a total of 10,850 sentences [63]. The duration and speaker information for the training and test splits are shown in Table 3.1. This dissection of speakers contains no overlap between the respective training and test sets. The trigram language model was constructed using the audio transcriptions, as well as other text corpora, resulting in 120,262 sentences and 2.5 million words [64].

Table 3.1: Amharic Dataset Information

Partition	# Male	# Female	Duration
Train	56	44	20 h 01 m
Test	14	10	0 h 43 m

3.1.2 Prior ASR Work

The prior work on ASR for Amharic was focused on improving output by exploring the use of acoustic, lexical, and language models units of varying sizes (e.g., syllables rather than phones, morphemes rather than words) [16, 64, 65, 66]. The most notable contribution is the effectiveness of using sub-word units as the basis for a language model, applying a lattice rescoring framework such that one pass can be made with a n-gram model followed by a sub-word unit LM. The most recent work [67] focuses on producing an ASR system with an acoustic model based on syllables, before their LM rescoring, using the Kaldi framework. The models used were a subspace Gaussian mixture model (SGMM) with maximum mutual information (MMI) and a DNN with state-level minimum Bayes risk (sMBR) criterion. The DNN had 7 layers, each with 1024 hidden units, with weight initialization from a Restricted Boltzmann Machine [68]. The SGMM+MMI combination [29] allows for the formation of numerous generative models with efficient training of the sub-states. The inclusion of sMBR into the DNN approach was found to be most effective [69] at determining sequence-discriminative criteria. Both approaches use the feature-space maximum likelihood regression speaker adaptation method [23] as a means of producing speaker-independent results.

3.2 Bemba

3.2.1 Language Description

The Bemba (ISO 693-3 bem) language is a member of the Bantu branch of the Niger-Congo language family spoken by approximately 5 million people, primarily in Zambia. The Bemba writing system is based on the Latin script, consisting of 23 characters to represent each phoneme in an injective fashion. There are 24 phonemes, 19 consonants and 5 vowels, and are classified into the syllable structure of: vowel, consonant, nasal, and glide. The corpus [70] was collected outside a closed environment via read speech from 10 fluent speakers, 6 male and 4 female, for a total of 10,956 sentences. The audio data was purposefully collected in an uncontrolled setting to induce noise and emulate a real-world ASR scenario; each utterance length is between 1 and 20 words. The duration and speaker information for the training and test splits are shown in Table 3.2. This subset of speakers contains no overlap between the respective training and test sets. The trigram language model was constructed using just the audio transcriptions (123,000, 27,000 unique, words), no additional improvement was found when using an additional dataset which totaled 5.8 million (189,000) unique words.

Table 3.2: Bemba Dataset Information

Partition	# Male	# Female	Duration
Train	5	3	14 h 20 m
Test	1	1	1 h 18 m

3.2.2 Prior ASR Work

Previous work on Bemba [70] used the DeepSpeech architecture [55, 71], which required an initial round of training on a large corpus of English followed by cross-lingual

via transfer learning to the small Bemba corpus. The DeepSpeech model was 6 layers: 3 fully connected, followed by a unidirectional LSTM, followed by 2 fully connected layers. The data was pre-processed to be all lower case and excluded any utterance longer than 10 seconds long.

3.3 Iban

3.3.1 Language Description

The Iban (ISO 693-3 iba) language is a member of the Malayo-Polynesian branch of the Austronesian language family spoken by approximately 1.5 million people, primarily in Borneo. The Iban orthographic system is based on the Latin script, consisting of 27 characters to represent a 1-to-1 character to phoneme mapping. There are 30 phonemes, 19 consonants and 11 vowel clusters, and are classified into the syllable structure of: vowel, consonant, nasal, and glide. The dataset [72] contains no mention of recording conditions or speaker proficiency, but consists of 23 speakers, 9 male and 14 female, for a total of 3,000 sentences. The duration and speaker information for the training and test splits are show in Table 3.3. This speaker partitioning contains no overlap between the training and test sets. The trigram language model was constructed using the audio transcriptions alongside additional text scraped from the internet, which totaled 2 million (37,000 unique) words.

Table 3.3: Iban Dataset Information

Partition	**# Male**	**# Female**	**Duration**
Train	7	10	6 h 48 m
Test	2	4	1 h 11 m

3.3.2 Prior ASR Work

Previous work on ASR Iban [73, 72] focused on data augmentation and cross-lingual transfer learning by leveraging similarities between Iban and Malay, a closely related language with more abundant data. Using Kaldi with feature enhancements similar to those used for Amharic, Section 3.1.2, the authors trained GMM, SGMM, and DNN ASR systems, yielding the lowest error rates with the former two architectures. Their work also notes the effectiveness of speaker adaptation through features like fMLLR in a GMM model, but ineffectual results within the SGMM and DNN.

3.4 Seneca

3.4.1 Language Description

The Seneca (ISO 693-3 see) language is a member of the Seneca-Cayuga branch of the Iroquoian language family spoken by around 50 elders and roughly 100 second language learners, primarily in western New York, United States, and Ontario, Canada. The Seneca orthography is based on the Latin script, consisting of 30 characters, which represent a 1-to-1 grapheme-to-phoneme mapping. The Seneca audio data consists of spontaneous speech recorded primarily in casual settings over several years from 11 speakers, 7 male and 4 female. The duration and speaker information for the training and test sets are shown in Table 3.4. This speaker partitioning does contain overlap between the respective training and test sets due to an in-balance between length of data per speaker, coupled with few total speakers. The trigram language model was constructed using a combination of transcripts from the training set and all other available written texts collected by linguists, missionaries, and anthropologists for a total of 49,051 (7,625 unique) words.

Table 3.4: Seneca Dataset Information

Partition	# Male	# Female	Duration
Train	7	4	9 h 47 m
Test	7	4	01 h 40 m

3.4.2 Prior ASR Work

The prior work for Seneca [8, 47] explores the WireNet, Kaldi GMM, and DeepSpeech frameworks. The WireNet architecture and staged pipeline, Section 2.8.4, produced better results than the DeepSpeech framework used in Bemba, Section 3.2.2, or the Kaldi implementation, although it was a more simplified version than Section 3.1.2.

3.5 Swahili

3.5.1 Language Description

The Swahili (ISO 693-3 swa) language is a member of the Bantu branch of the Niger-Congo language family spoken by approximately 16 million people, primarily in Tanzania. The Swahili writing system is based on the Latin script, consisting of 41 characters, 36 consonants and 5 vowels, which represent a 1-to-1 grapheme-to-phoneme mapping. The Swahili audio data [74] consists of 3.5 hours of read speech from 5 speakers, combined with 8.2 hours of broadcast news data from an unknown number of speakers, for a total of 12,171 sentences. As such, the quality and speaker information are generally unknown, therefore the segregation of the training and test splits cannot be determined, but characteristics are shown in Table 3.5. The trigram language model was constructed using the audio transcriptions alongside additional text scraped from the internet, which totaled 400,000 (81,223 unique) words.

Table 3.5: Swahili Dataset Information

Partition	# Male	# Female	Duration
Train	N/A	N/A	9 h 54 m
Test	N/A	N/A	1 h 50 m

3.5.2 Prior ASR Work

This was the first work looking to explore ASR on the language of Swahili; the authors evaluated their corpus using a similar set up to the Amharic language, Section 3.1.2.

3.6 Vietnamese

3.6.1 Language Description

The Vietnamese (ISO 693-3 vie) language is a member of the Vietic branch of the Austro-Asiatic language family spoken by approximately 70 million people, primarily in Vietnam. The Vietnamese writing script is based on the Latin script, consisting of 91 characters to represent each phoneme in an injective fashion. There are 99 phonemes total, 26 consonants and 73 vowels, and a space in the Vietnamese language indicates a syllable break and not necessarily a word as in English. The corpus [75] was collected in a closed environment using read speech by 65 native speakers, 34 male and 31 female, for a total of 12,420 sentences. The duration and speaker information for the training and test splits are shown in Table 3.6. This subset of speakers contains no overlap between the respective training and test sets. The trigram language model was constructed using the audio transcriptions alongside additional text scraped from the internet, which totaled 20 million (143,206 unique) words.

Table 3.6: Vietnamese Dataset Information

Partition	# Male	# Female	Duration
Train	22	14	14 h 55 m
Test	12	7	0 h 45 m

3.6.2 Prior ASR Work

Luong and Vu [75] created 4 Kaldi models: GMM, GMM+MMI, GMM+SAT, and a hybrid HMM-DNN model with fMLLR features. Similar to Amharic, Section 3.1.2, they used the same feature setup in all scenarios, but their DNN was only 3 layers with 300 hidden units, with no mention of weight initialization. The authors do employ data augmentation, using the Kaldi pitch augmentation feature as well as tree-clustering of the phones.

3.7 Wolof

3.7.1 Language Description

The Wolof (ISO 639-3 wol) language is a member of the Senegambian branch of the Niger-Congo language family spoken by approximately 10 million people, primarily in Senegal, the Gambia, and Mauritania. The Wolof orthography is based on the Latin script, consisting of 29 characters with a mostly 1-to-1 character-to-phoneme mapping. There are 38 phonemes, 29 consonants and 9 vowels, and the pronunciation length is determined by the number of repeated characters. The dataset [76] was collected in a controlled environment using read speech from 18 native speaker, 10 male and 8 female, for a total of 15,998 sentences. The duration and speaker information for the training and test splits are shown in Table 3.7. This subset of speakers contains no overlap between the respective training and test sets. The trigram language model was constructed on the transcripts of the audio, as well as a combination of

physical books and data scraped from the internet, for a total of 601,609 (29,148 unique) words.

Table 3.7: Wolof Dataset Information

Partition	# Male	# Female	Duration
Train	8	6	16 h 49 m
Test	1	1	0 h 55 m

3.7.2 Prior ASR Work

This was the first work looking to explore ASR on the language of Wolof; the authors evaluated their corpus using a similar set up to the Amharic language, Section 3.1.2. In a subsequent paper, the authors found that modeling vowel length contrasts improved word error rate [77].

Chapter 4

Methodology

As there are numerous corpora spanning varying morphologies and ASR implementations, it will be beneficial to standardize the results across these languages to determine what combination of input feature, acoustic, and language model can produce the best result or if the combination differs per language structure.

4.1 Language Comparison

4.1.1 Average Utterance Length

As described prior, the ability of a DNN to aptly model a speech signal is dependent on the width of the layers, but wider layers require more time to reach convergence. Therefore, if we can simply reduce the length of the audio signal, there is less need for such wide of layers. Each language was measured for mean utterance length (MUL), with the intention to create data subsets with a MUL less than 5, 10, or 15 seconds to determine the correlation between MUL and WER, as studies have indicated natural language understanding can occur in as few as 6 words [78].

4.1.2 Quality Measures

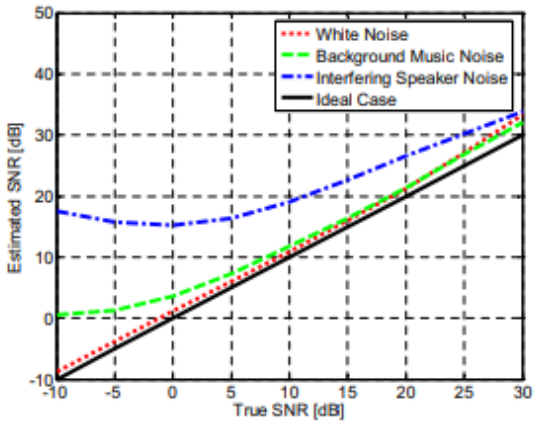
Another potential insight into the language differences is recording quality; some languages are purposefully recorded in a conversational tone with extraneous noise

unfiltered, others with studio quality sound equipment, while others still use radio or television broadcasts. Each recording condition will contain some measure of background noise, and although preliminary research indicates that noise can be naturally removed [48], human speech comprehension is based on the recognition of both voiced and unvoiced pieces. Two measures of quality were conducted on the languages: National Institute of Standards and Technology's (NIST) speech Signal to Noise Ratio (SNR) and Waveform Amplitude Distribution Analysis (WADA) SNR. General SNR is defined through Equation 4.1, where the signal $x(t) = s(t) + n(t)$, these two tools work to evaluate the SNR of an entire audio signal.

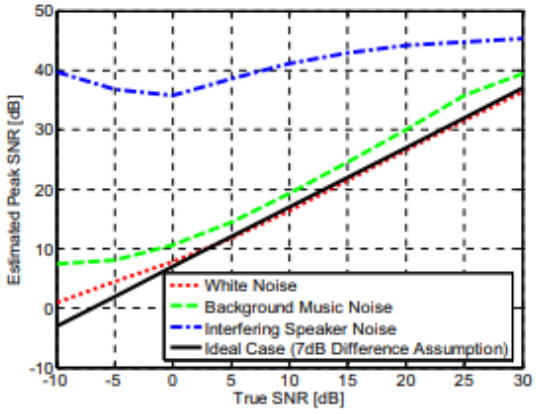
$$SNR_{dB}(x) = 10 \log_{10} \frac{Power(s)}{Power(n)} \tag{4.1}$$

NIST's SNR measurement tool uses a sequential GMM to model the speech data, before being evaluated by the Kolmogrov-Smirnov statistic for goodness of fit. If a reasonably good fit is achieved, the mixtures are estimated using the standard Expectation Maximization (EM) steps, producing a quality estimate.

WADA's SNR algorithm examines the gamma distribution of the amplitude, noting that the probability density function of said gamma distribution can be shaped to estimate SNR [3]. Through an experiment with heavy noise dilation on a news database, Kim and Stern [3] found that the WADA algorithm more closely mimicked the expected speech quality, Figure 4.1, with a separate group confirming [79] against a different corpus.



(a) *Results with the WADA-SNR algorithm*



(b) *Results with the NIST STNR algorithm*

Figure 4.1: Comparison of the WADA SNR algorithm and the average estimated NIST SNR against an artificially corrupted database. [3]

4.2 Kaldi

There were several Kaldi implementations presented by the prior ASR work [67, 73, 72, 8, 47, 75, 76], but we focused on the well documented version in Gauthier et al. [76]. The models were cascaded together, beginning with 13 MFCCs, their delta delta coefficients, transformed via LDA, MLLT, and fMLLR. These features were passed into triphone GMM models with 3,401 context-dependent states and 40k Gaussians. The SGMM was trained and rescored a total of 8 times, broadening the GMM sub-

space construction, before final rescoring from MBR and FMMI [80]. The DNN was built on 6 hidden layers of 1024 units and trained using 11 consecutive frames and state-level minimum Bayes risk (sMBR) criterion, with weight initialization from RBMs, before final finetuning using Stochastic Gradient Descent.

We also investigated Kaldi with data augmentation, similar to Luong et al. [75], in order to explore whether addition data will improve ASR accuracy within this framework.

4.3 WireNet

The WireNet architecture [8] was capable of producing state-of-the-art results on the low-resource language of Seneca, we investigate whether these improvements will extend to other available ASR corpora with varying linguistic properties and corpus features, such as speaker pool size, speaker diversity, and SNR.

4.3.1 Transfer Learning

The first step in the WireNet pipeline is transfer learning from a high resource language, typically English. Transfer learning has been seen as critical to a low-resource language ASR system [34, 81], but produces a large overhead whenever the internal architecture changes, requiring re-learning for this new structure.

4.3.2 Data Augmentation

The second stage in the aforementioned pipeline is inclusion of additional data in the training set as a means of artificially boosting the amount of available audio to be able to emulate a higher resourced language.

4.3.2.1 Speech Synthesis

In a low-resource scenario, not only is the number of utterances limited, but also the speakers themselves. These corpora have taken great care to isolate the training and test set speakers, barring Seneca, limiting the already low amount. Textual data, however, is often prevalent for these languages; therefore, we might be able to synthesize a speaker from the training set from their audio samples and reapply their voice to a new textual utterance. This will improve not only the dataset duration, but also quality as the vocabulary will increase.

4.3.2.2 Pitch/Time Shifting

More simple methods of data augmentation keep the same linguistic content, altering the phonetic and acoustic properties. Here we base the augmentation methods on those from the Jimerson et al. [47, 8], adjusting the fundamental frequency and speaking rate. Pitch augmentation was performed by varying the frequency by a randomly chosen octave ranging from 0.10 to 0.25, with a step size of 0.05. Speed shifting was performed by re-sampling the audio at a different, randomly chosen frequency ranging from 0.75 to 1.25, with a step size of 0.05. Each utterance in the training set was distorted randomly 10 times and added alongside the original data, totaling an average increase of 1000%.

4.3.3 Architecture Exploration

The original architecture from WireNet, Figure 2.4, depicts 5 bottleneck block layers, where each bottleneck contained 9 incrementally varying, odd width kernel sizes. The author mentions that these filter widths are chosen to pick up both short- and long-term dependencies [8] but contains no mention of how these numbers were selected. Additionally, the number of filters per convolutional layer could also be an area of improvement, as inverted linear bottlenecks [82] have shown to produce effective con-

vergence. Therefore, we aim to determine the optimal width, depth, and bottleneck size for these various languages in a hope to understand the author's numerical selections. Additionally, we attempt to arrange these bottleneck blocks in various schema from other state-of-the-art producing architectures such as U-Net [4], Selective Kernel Networks [83], or Time Delay Neural Network [84].

4.3.4 Feature Comparison

Input feature choices are incredibly broad, with numerous statistical analyses often applied after the original extraction. There are several main categories: raw audio, log Mel filterbanks, MFCCs, and speaker adaptive methods.

Raw audio is often only passed into models built to specifically extract the features through a LSTM or RNN based system [57, 14] and rarely into a purely convolutional architecture as the overhead is quite high and does not produce enough statistical improvements to warrant inclusion.

Log Mel filterbanks, MFCCs, Perceptually based Linear Prediction, and other features are human interpretations of the weighted representation of the audio signal to emphasize the voiced conditions. There is often very little difference between these features, but no standard has been accepted and thus will be compared.

Feature space maximum likelihood linear regression and vocal tract length normalization efforts note the difference in vocal tract length per person, meaning each speaker's resonant frequency varies slightly. These efforts work to calculate a scaling factor such that all speakers have a similar fundamental frequency. Although there is previous evidence [73, 72] this does not produce significant results in DNN systems, it is a staple of GMM toolkits.

4.4 Speaker Re-partitioning

In addition to the toolkit specific adjustments, we also want to examine the importance of the dataset construction. Specifically noted in the corpora statistics is that the training and test sets contain disjoint speakers. However, in Seneca, as in most endangered languages, there are simply not enough speakers to create speaker-disjoint training and testing sets. We tested both purposeful withholding of speakers, alongside purely random construction to investigate the effectiveness of speaker overlap between the two sets. An important distinction is that the audio transcriptions will not be duplicated in any manner, the utterances maintain their uniqueness such that the systems will not be overfit to one sentence.

4.5 Language Model Exploration

Alongside the acoustic model exploration, the language model rescoring is essential towards quality results from the system. On top of the standard n-gram models, we aim to investigate a LSTM LM [43, 54] capable of producing state-of-the-art results across numerous systems [85, 14].

Chapter 5

Results

5.1 Kaldi Results

5.1.1 Overall

The normalization of the results across these various languages begins with the standardized experiments with the Kaldi setup, these results are shown in Table 5.1. The top two architectures are displayed, the SGMM and DNN variants, with the best WER taken from each model's most successful iteration.

Table 5.1: Overall Kaldi results for the two best architectures across all languages.

Language	**Model**		**Relative Reduction in WER**
	SGMM	DNN	
Amharic	8.4	7.5	10.71
Bemba	58.4	53.4	8.56
Iban	16.4	15.1	7.93
Seneca	33.9	30.6	9.73
Swahili	27.3	26.5	2.93
Vietnamese	9.7	9.5	2.06
Wolof	25.1	24.9	0.80

Notably, for every model the DNN performed best, with often improvements up to

8% over the SGMM. Additionally, the results for the Bemba and Iban are the lowest word error rates uncovered thus far: 54.78 [70] vs. 53.4 and 18.1 [72] vs. 15.1, with the Vietnamese matching the state-of-the-art result to the tenth decimal place, 9.48 [75] vs 9.53. Of note, this was the best non-WireNet Seneca result produced, 42.1 [8] vs. 30.6. For the other languages, this was the recipe used by the authors [76] and thus no improvements found.

5.1.2 Data Augmentation

The original Vietnamese work [75] produced a model with equal performance to the Kaldi recipe above, but doing so required the use of data augmentation, noting a 29% improvement (3.86 WER). As such, we applied augmentation, Section 4.3.2, to the language of Wolof. This method was not applied to other languages due to the increased training time required for the chosen Kaldi DNN model, noting an increase of 7000% in the system's training time.

Wolof	**Model**	
	SGMM	DNN
W/o Augmentation	25.1	24.9
W/Augmentation	23.0	22.4

Table 5.2: Kaldi results for the two best architectures across the Wolof language with data augmentation.

The augmentation method used was slightly different from Luong and Vu, but still produced an 8.9% decrease (2.5 WER).

5.2 WireNet

5.2.1 Overall Results

The normalization of results continues with the second architecture type, WireNet; these results are shown in Table 5.3.

Table 5.3: Overall WireNet results across all languages.

Language	Kaldi Best	WireNet[1]	Relative % Change
Amharic	7.5	17.3	56.65
Bemba	53.4	64.4	17.08
Iban	15.1	26.6	43.23
Seneca	30.6	24.3	-25.93
Swahili	26.5	37.1	28.57
Vietnamese	9.5	18.8	49.47
Wolof	24.9	29.9	16.72

This table is incredibly insightful into the results produced for the languages: flagging Seneca as the only language coming within 15% of the state-of-the-art. Such a result makes sense given that the authors tailored the architecture to the Seneca morphology, but also lends an exploration into the dataset construction, Section 4.4.

5.2.2 Architecture Exploration

As the original architecture was apparently so heavily tuned on Seneca, the architecture was explored through a parameter sweep to determine if any potential improvements could be made. The language of Swahili was chosen due to the similar training/test split lengths to Seneca, and the sweep begun, with the results shown in Table 5.4.

[1]Indicates modified WireNet, see Section 5.2.2.

Table 5.4: WireNet architecture exploration for Swahili, varying the width and depth of the system.

Depth	Width	WER	CER
5	9	42.384	19.281
6	9	46.707	20.269
7	9	51.277	22.037
8	9	56.271	28.412
4	9	42.809	18.032
3	9	43.546	18.916
4	10	42.263	17.958
4	8	45.970	20.286
4	11	40.908	17.427
4	15	39.663	17.223
4	**21**	**37.136**	**16.47**
3	21	42.418	19.362

Analyzing the table indicates that Swahili, an agglutinative, morphologically rich language, performed best with a shorter, wider network; this can apply to the similarly morphologically complex African languages of Amharic and Wolof. Through experimental results, this modified WireNet of a depth of 4 and width of 21 produced marginally (1-3%) better results across the board no matter which language was tested.

Additionally, the bottleneck size was investigated, as an inverted linear bottleneck has been shown to improve convergence time [82], with a trade-off of memory usage, shown in Figure 5.1.

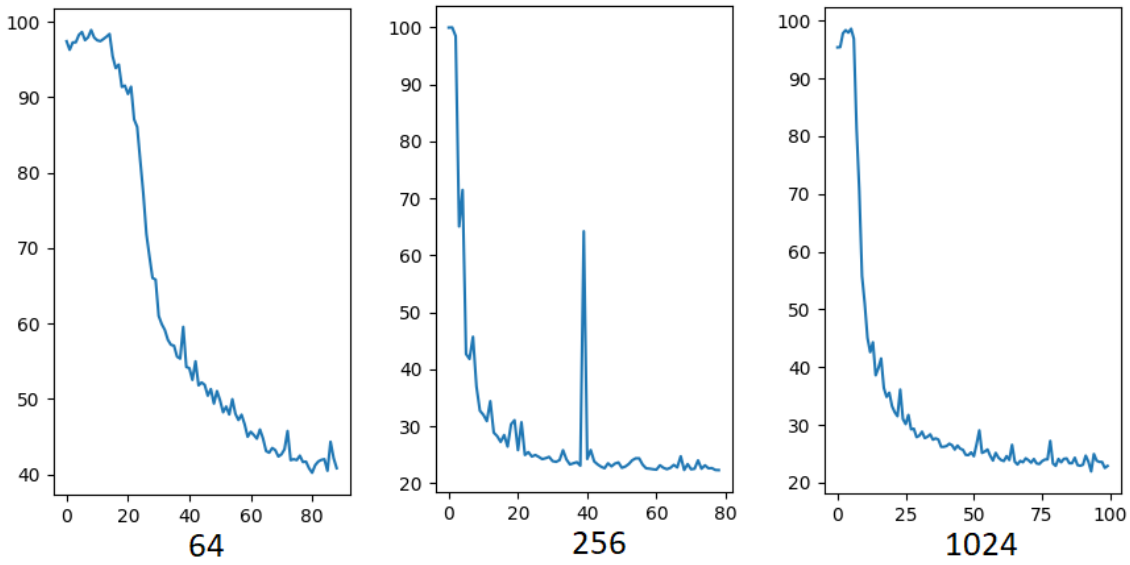


Figure 5.1: CER vs. training epochs of the Swahili language at specific bottleneck depths.

This exploration shows that there is a point at which the error rate converges more quickly, around a bottleneck depth of 256, and after that the increase can actually be harmful. Note that this did not improve the WER of the system, only the convergence time; it did however increase training time as the GPU memory required for these larger widths reduced the potential batch size. During this exploration it became evident that the transfer learning step introduced by Wav2Vec [57] and utilized by WireNet [8] is not helpful towards the speed of convergence; the majority decreases during the augmentation step; explored further in 5.2.3.

The architecture was additionally structured in a similar manner to U-net [4], Figure 5.2.

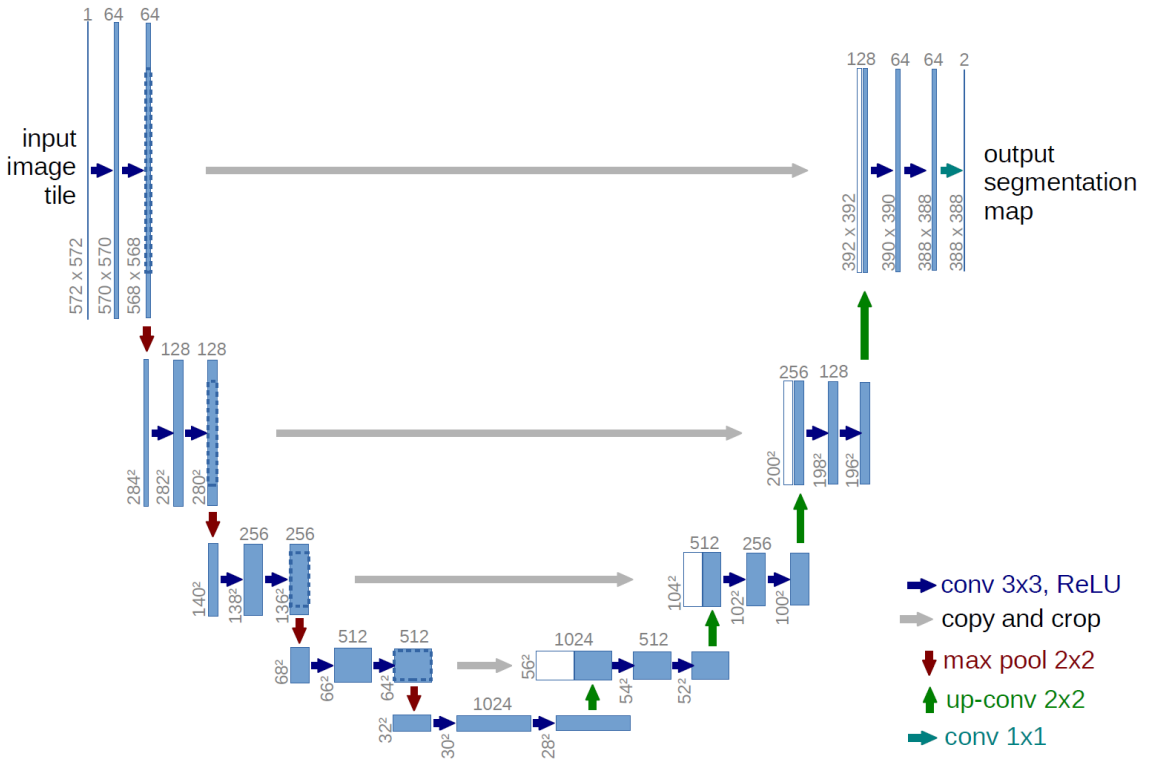


Figure 5.2: U-Net architecture where the convolutional size increases to a maximum of 1024, before reducing back to the input size. [4]

To reproduce the U-Net state-of-the-art models in a different domain, the bottleneck blocks were cascaded in a similar style to Figure 5.2, with evaluation performed on the language of Swahili, shown in Table 5.5.

Table 5.5: WireNet results for the Swahili language with U-Net styled architecture.

Language	**WER**
Swahili	67.83

Such an architecture was unsuitable for this application, as the model parameters were too large, with not enough training data or time available for convergence to occur.

5.2.3 Transfer Learning

Transfer learning is often seen as critical to the success of a low-resource language ASR system [34, 81, 14, 15, 72], but when performing an architecture exploration such as above, it is incredibly time consuming to re-train the model on this high-resource dataset to where suitable results have been attained. Therefore, we investigated the efficacy of said step.

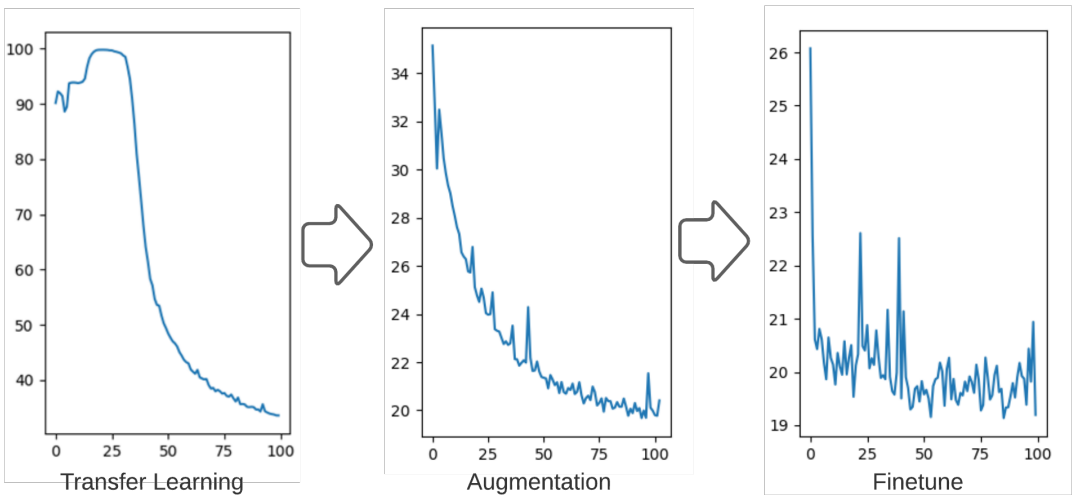


Figure 5.3: CER vs. training epochs through the stages of training the Swahili language with transfer learning.

During the transfer learning stage from a high-level language, the CER begins at a less than 100% because of this initialization; however, due to the dissimilarity between languages, the first few epochs are seen re-learning these weights. As such, the CER increases initially, before decreasing once these prior weights are overwritten. Essentially this step just trains directly on the clean, unaugmented data itself for an extra stage. Beginning training on the augmented data, Figure 5.4, removes this superfluous step and achieves the same end word error rate.

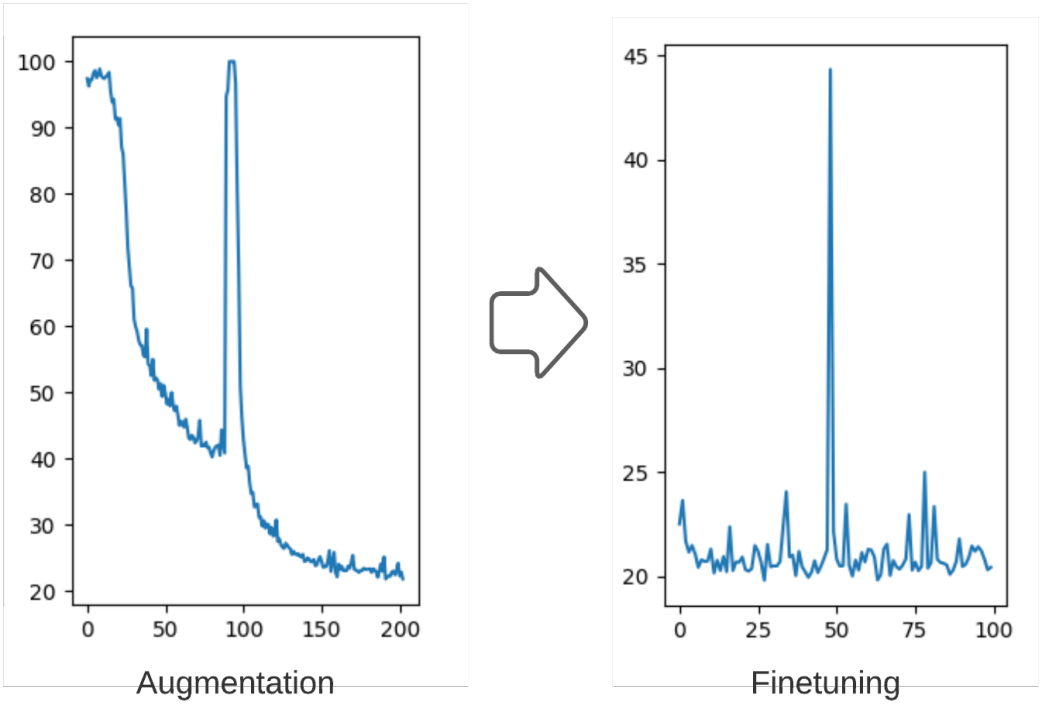


Figure 5.4: CER vs. training epochs through the stages of training the Swahili language without transfer learning.

This breakthrough also unveiled another: the finetune stage was stagnating once the model was trained to convergence on the augmented data. Applying a learning rate scheduler to the CTC loss, potentially allowing for the finetune stage to better suit its name, but in actuality indicating a more suitable early stopping point.

5.2.4 Feature Comparison

The ability to model the different linguistic properties of languages is impacted by the input features used, shown in Table 5.6.

Table 5.6: Feature Comparison of Languages

Language	Feature	WER	CER
Seneca	MFCC	29.9	17.5
Seneca	FBANK	**24.3**	**13**
Swahili	MFCC	**51.277**	**22.037**
Swahili	FBANK	56.271	28.412
Amharic	MFCC	18.233	9.263
Amharic	FBANK	**17.346**	**8.962**
Vietnamese	MFCC	18.829	11.495
Vietnamese	FBANK	**18.130**	**9.621**

As one goal is to standardize the model parameters, and input features can take many forms, results such as Table 5.6 indicate that the filterbank features themselves, without the additional discrete cosine transform, perform better. This holds for 5 of the 7 languages tested, although arguments may be made for quality and extraneous factors being the reason for better WireNet performance in Swahili and Wolof as opposed to the input feature.

Additionally, the Kaldi introduced feature of fMLLR was used on the Wolof dataset, with the effects of speaker normalization evident on the architecture performance, shown in Table 5.7.

Table 5.7: Feature Comparison of Wolof

Feature	WER	CER
MFCC	**29.882**	**11.149**
FBANK	30.331	11.792
fMLLR	35.922	13.689

Similar to the work on Iban [73, 72], the application of speaker normalization did

not improve the system performance, heavily in the opposite direction in fact. As other methods are attempted to introduce speaker normalization, Section 4.4, remove this feature from the Kaldi schema may prove fruitful.

5.3 Language Comparison

To attempt to clarify the reasoning behind design choices such as input feature representation or results such as word error rate, the quality of the datasets was evaluated using the standard signal to noise ratio calculators, displayed in Table 5.8 alongside visually in Figures 5.5 and 5.6.

Table 5.8: SNR overview per language.

Language	**NIST SNR**		**WADA SNR**	
	Train	Test	Train	Test
Amharic	4.19 ± 3.83	18.80 ± 5.69	4.85 ± 3.37	17.978 ± 7.24
Bemba	32.46 ± 12.01	50.65 ± 33.92	27.47 ± 9.75	36.27 ± 22.52
Iban	24.51 ± 8.43	18.54 ± 5.28	22.65 ± 8.79	17.23 ± 4.32
Seneca	24.96 ± 12.85	23.51 ± 21.07	25.19 ± 13.14	25.72 ± 24.02
Swahili	14.84 ± 12.23	13.66 ± 7.13	16.77 ± 12.22	15.68 ± 5.92
Vietnamese	41.48 ± 9.70	57.32 ± 31.86	37.68 ± 11.05	55.62 ± 36.37
Wolof	35.92 ± 5.59	45.03 ± 34.99	35.39 ± 3.77	38.08 ± 14.59

We see that Bemba, Iban, and Wolof have comparable SNR under both methods of calculation, while the SNR for Amharic is substantially lower than the others under the NIST method but comparable to Iban under the WADA method. We also observe much less variation in SNR for Iban and Amharic than for the other languages, while the Seneca, Wolof, and Vietnamese contain a great measure of variability, specifically in the test sets.

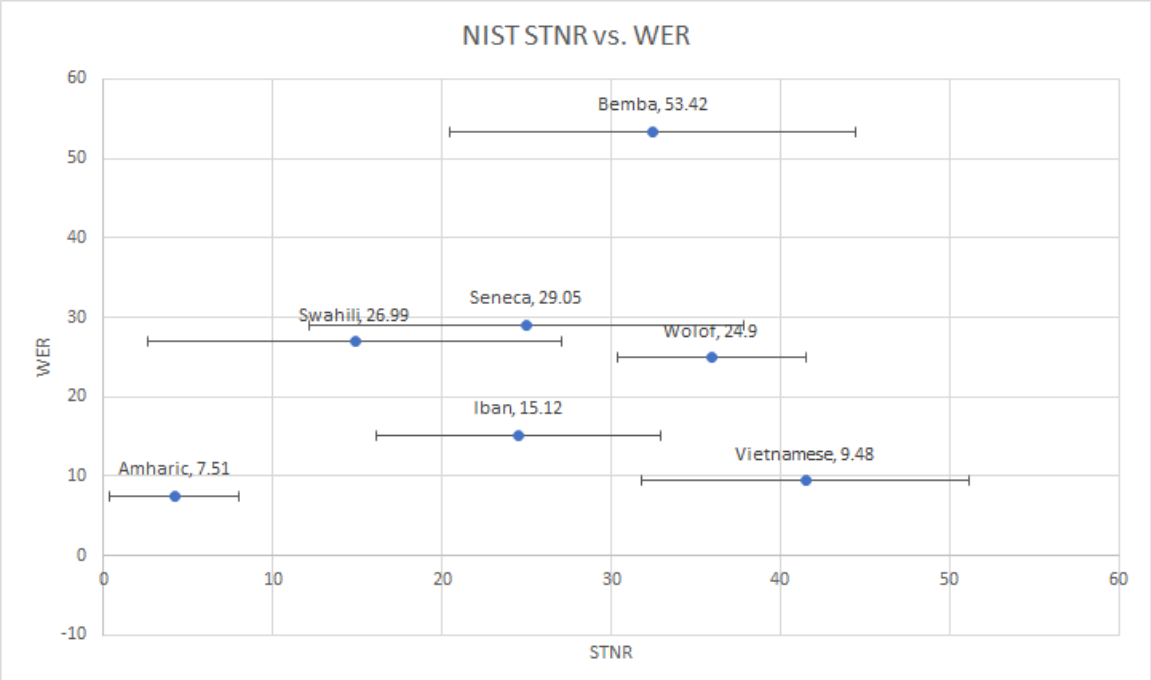


Figure 5.5: Best produced WER vs. NIST SNR across all languages, training set depicted.

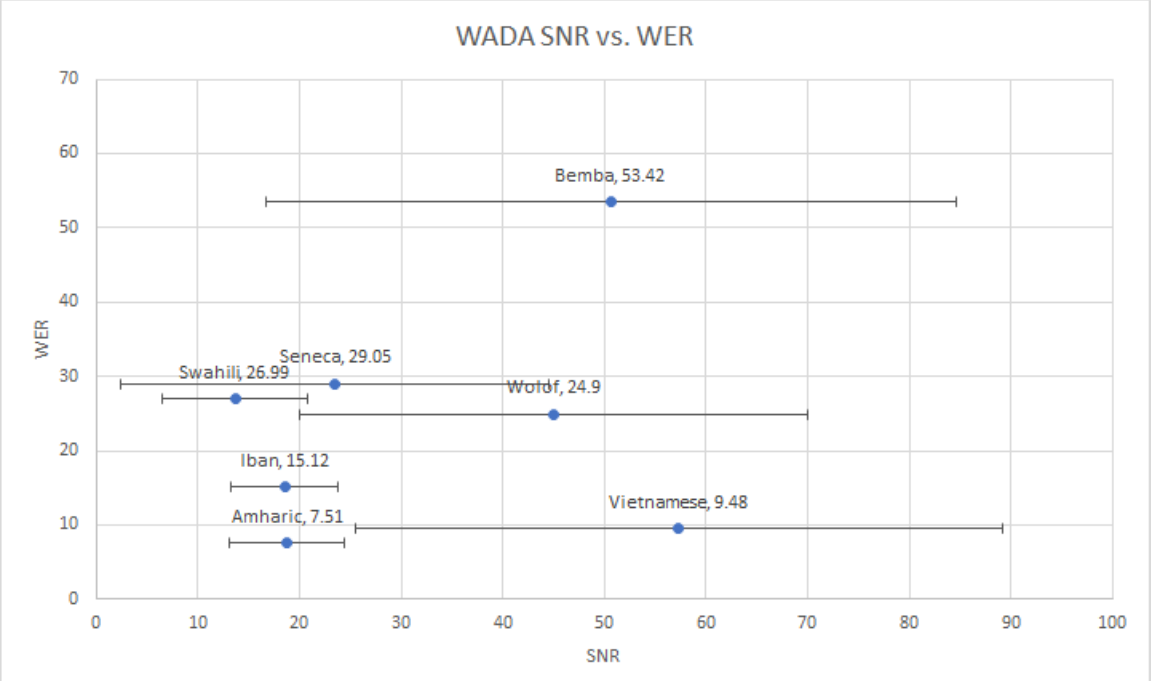


Figure 5.6: Best produced WER vs. WADA SNR across all languages, training set depicted.

There does not appear to be an indication between dataset quality and word error rate; as Li et al. hypothesized [48], the DNN naturally normalized the heterogeneous data.

5.4 Language Model Exploration

A neural language model was attempted using the Neural Network Language Model Toolkit in TensorFlow [86] on the Wolof language. Two models were trained: a Vanilla RNN and a LSTM with projection; their results are in Table 5.9.

Table 5.9: Neural language model perplexity for the language of Wolof.

Model	**Perplexity**
Trigram (Baseline)	**301**
Vanilla RNN	594
LSTM	572

The baseline language model is a trigram model evaluated by Gauthier et al. [76], which was able to outperform both neural models, indicative via the number of words in the corpus, 106k, vs. 933k or 133M [86].

5.5 Speaker Overlap

The Seneca dataset contains speaker overlap within the training and test sets, while the 6 other languages explicitly do not employ such strategies. An exploration into the effects of speaker overlap on the WireNet architecture was performed, with results on all languages displayed in Table 5.10. The Seneca was not performed in the disjoint state due to speaker imbalance such that no appropriate construction could be made.

Language	Model	WER	
		Disjoint	**Overlap**
Amharic	SGMM	8.4	4.8
	Kaldi DNN+sMBR	**7.5**	**4.1**
	Modified WireNet	17.4	15.0
Bemba	SGMM	58.4	13.9
	Kaldi DNN+sMBR	**53.4**	**12.3**
	Modified WireNet	64.4	48.8
Iban	SGMM	16.4	13.0
	Kaldi DNN+sMBR	**15.1**	**12.9**
	Modified WireNet	34.3	19.8
Seneca	SGMM	-	33.9
	Kaldi DNN+sMBR	-	30.6
	WireNet	-	**24.3**
Vietnamese	SGMM	9.7	2.5
	Kaldi DNN+sMBR	**9.5**	**2.2**
	Modified WireNet	18.8	14.6
Wolof	SGMM	25.1	28.3
	Kaldi DNN+sMBR	**24.9**	27.4
	Modified WireNet	29.8	**14.3**

Table 5.10: Word error rate (WER) for each language under the three architectures and two train/test split settings: the original, in which no speaker has utterances in both the train and test sets (Disjoint), and a new split in which each speaker's utterances are split between the training and test sets (Overlap).

The test set arrangement of no specifically held out speakers provides incredible improvements across all languages, primarily within the Kaldi DNN. Specifically, the Bemba WER drops from 53.4 to 12.3, a 77% decrease, and the Vietnamese has an

almost unbelievable 2.2% WER, although their word boundaries were more syllabic [75], this is still impressive. The two outliers are the languages of Seneca and Wolof, where the WireNet models performed strikingly better than Kaldi.

Given the vast reductions in WER using this method, we investigated at which point the test set construction could be hindered by containing too few of the speakers. With this in mind, we performed specific speaker holdouts from those whose total combined utterance lengths were less than the test set time, such that the test set may contain more than one speaker. The results for the Bemba, Seneca, and Wolof languages are present in Tables 5.11, 5.12, 5.13 and Figures 5.7, 5.8, 5.9, respectively.

Speaker Withheld	**Duration (s)**	**% of Total**	**% of Test**	**WER**
1	24670.82	43.84	-	-
3	14854.03	26.40	-	-
5	7310.515	12.99	-	-
4	3326.315	5.91	71.08	8.6
6	1951.42	3.47	41.70	29.22
7	711.5254	1.26	15.20	13.43
8	189.3953	0.34	4.05	14.1
9	349.9815	0.62	7.48	15.01
10	218.1657	0.39	4.66	11.82
12	2686.953	4.78	57.41	33.97
None	-	-	0	12.32
6, 12 (default)	4638.373	-	100.00	53.42
Even	-	-	-	21.98

Table 5.11: Determining the impact of holding out each speaker for the Bemba language.

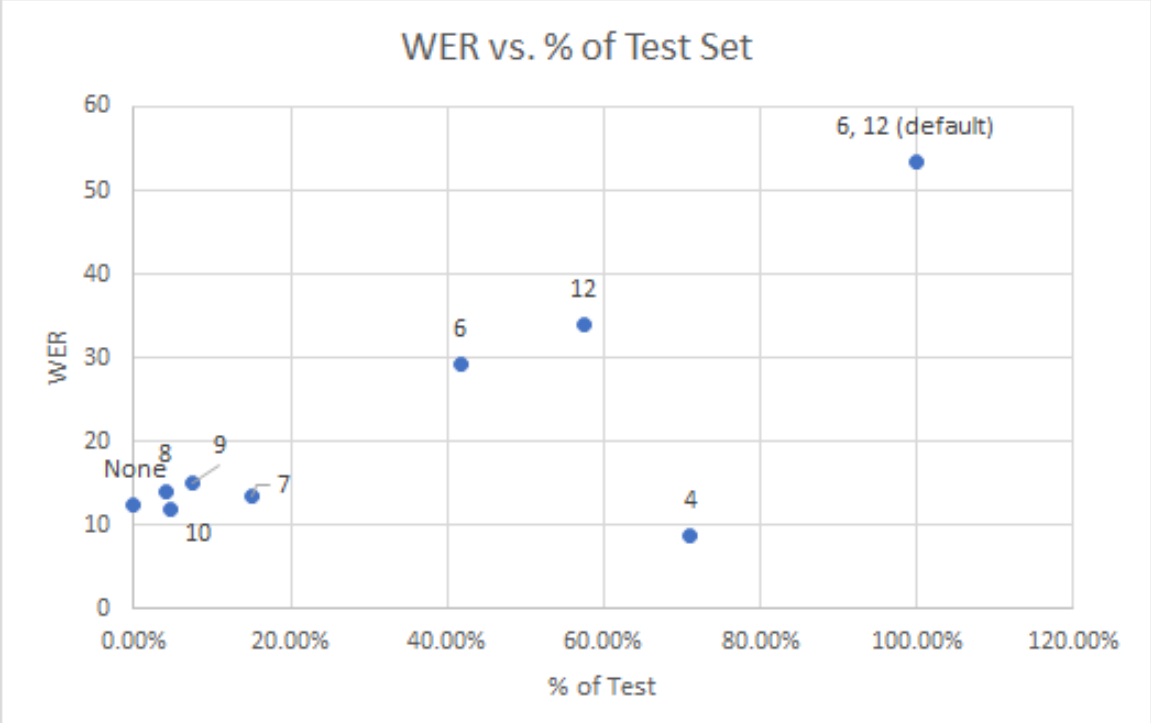


Figure 5.7: WER vs. % of Test Set for the Bemba Language.

There is a notably linear relationship between the amount of test set held by one speaker and the WER of the ASR system within Bemba. Whenever there is no regularization applied to the test set and utterances are selected randomly, we see a marked improvement as opposed to whenever the test set is held by 40% or 60% of one speaker. There is the outlier of Speaker #4 who produces the lowest WER of the tested Bemba system while controlling 71% of the test set.

Given the similarities between the Bemba and Seneca languages, their recording conditions, number of speakers, and overall audio length, this experiment was duplicated on Seneca.

Speaker Withheld	Duration (s)	% of Total	% of Test	WER
1	19762.70	47.94	-	-
2	11081.68	26.88	-	-
3	3476.26	8.43	0.58	26.38
4	2671.29	6.48	0.45	24.84
5	945.81	2.29	0.16	33.23
6	840.42	2.04	0.14	28.14
7	200.63	0.49	0.03	30.48
8	95.54	0.23	0.02	29.13
9	913.55	2.22	0.15	27.25
10	222.39	0.54	0.04	30.14
11	2099.39	5.09	0.35	38.65
None	6000.00	-	0.00	30.60

Table 5.12: Determining the impact of holding out each speaker for the Seneca language.

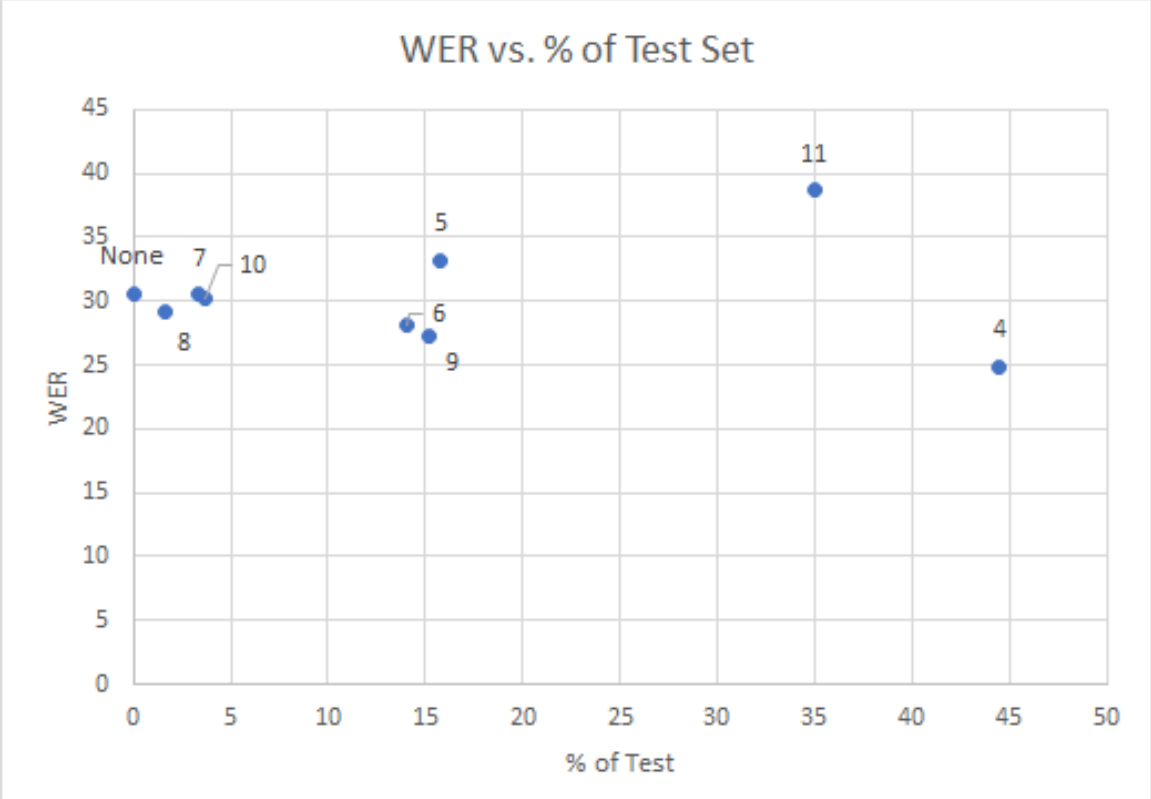


Figure 5.8: WER vs. % of Test Set for the Seneca Language.

Such a linear relationship is also seen in the Seneca language; however, this is less of a slope and more of a constant line. There is once again an outlier of Speaker #4 who produces the lowest WER of the tested Seneca system while controlling 44.5% of the test set. Additionally, this result from Speaker #4 comes incredibly close to the WireNet state-of-the-art result of 24.3 WER. There is no indication that holding out specific speakers has a beneficial effect on the overall WER of the system, but for assurance we tested again on the similar language of Wolof.

Speaker Withheld	Duration (s)	% of Total	% of Test	WER
1	4327.68	6.77	86.55	29.91
2	4226.22	6.61	84.52	25.34
4	4788.99	7.49	95.78	36.34
5	906.99	1.42	18.14	27.27
7	4129.59	6.46	82.59	28.87
8	4274.32	6.69	85.49	24.81
9	4903.53	7.67	98.07	38.02
10	2412.76	3.78	48.26	26.37
11	4697.13	7.35	93.94	31.17
12	4569.61	7.15	91.39	28.29
13	4803.69	7.52	96.07	27.55
14	4024.33	6.30	80.49	31.51
15	4237.14	6.63	84.74	24.15
16	3894.48	6.09	77.89	33.80
17	3796.23	5.94	75.92	31.68
18	3919.57	6.13	78.39	28.83
5, 10 (Default)	3319.75	5.19	100.00	24.90
None	3350.00	5.24	0.00	27.40

Table 5.13: Determining the impact of holding out each speaker for the Wolof language.

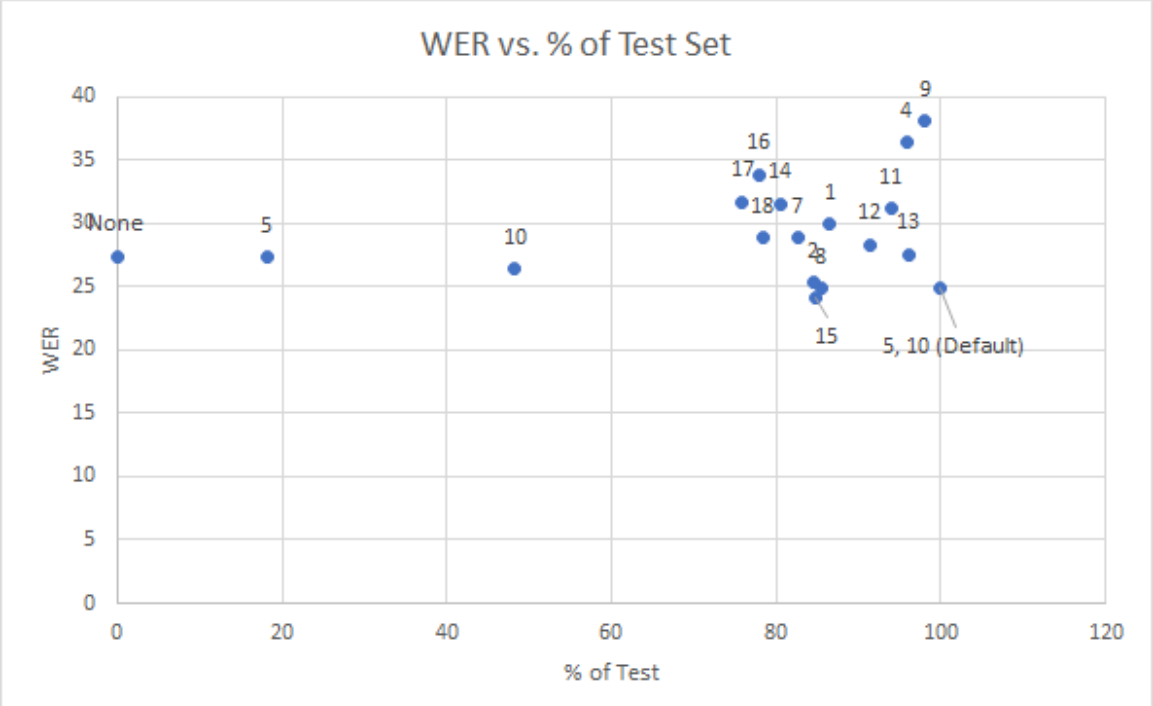


Figure 5.9: WER vs. % of Test Set for the Wolof Language.

The Wolof language can clearly indicate, similar to the Seneca language, that there is a WER threshold reached by the system, and although there are variations according to the percentage of the test set, no improvements seen. This raises the question of why the Bemba language performs so excellent with the overlap, leading us to the comparison of the SNR, 5.6. In a low-resource scenario with a high SNR due to poor recording conditions, overlapping the speakers in the training and test set can provide noticeable improvements in the Kaldi framework. In the WireNet architecture, this speaker enhancement trait allows for appreciable improvements across the board, yet they fall short of the state-of-the-art, but it is an effective tool to potentially improve accuracy greatly.

Chapter 6

Conclusions

6.1 Conclusions

The goal of this thesis is to develop a one-stop shop knowledge base of properly applying the state-of-the-art toolkits to low-resource languages. We explored architecture configurations for a cascaded hidden Markov model-based solution using statistical and deep learning methodologies. In addition, we propose improvements to a novel, fully convolutional neural network model that allows for the skipping of the time-consuming transfer learning stage, as well as general architecture adjustments which better suit an array of various morphological languages. We evaluated the effectiveness of various input features, acoustic, and language models to determine the efficacy of each component's various derivatives. The results show that the log Mel filterbanks are generally most effective at the convolutional level, while speaker adaptive methods perform better in a SGMM. Additionally, the combination of a simple DNN coupled with statistical methodology like state-level minimum Bayes risk allows for state-of-the-art calculation across the board.

We also note the use of data re-partitioning where utterances are withheld for a test set as opposed to speakers themselves. This allowed for the acoustic models to vastly improve their ASR capabilities, with some languages noting a 77% improvement in word error rate. We note that six of these seven languages, while having

few acoustic training resources, are widely spoken and have established written traditions adequate to support the training of large language models and the collection of additional data. Any ASR system built for these languages should be robust to speaker variation. A substantial majority of the world's 7000 languages, however, are endangered and in need of documentation and preservation, much like Seneca. Architectures designed specifically to be speaker independent may not be the best option for the documentation of languages with very few speakers.

6.2 Future Work

- Continued experimentation with these architecture constructions and others, e.g., Kaldi's Time Delay Neural Network, for available small corpora.
- Additional work with data augmentation as there are noted improvements in acoustic modeling systems.
- Further investigation into speaker overlap in the train/test set while maintaining utterance uniqueness, including technologies such as speech synthesis.
- Multi-lingual sequence-to-sequence models have shown to be a promising up-and-coming technology and may improve the low-resource field.

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